



Parameter Estimation in Coupled Models : Opportunities and Challenges

A talk on “Model Development and Analysis” MAPP webinar conference, 11 Dec., Washington DC, USA

Shaoqing Zhang
GFDL/NOAA

Co-Work with:

Z. Liu (Wisconsin),

X. Wu & X. Zhang (visit),

X. Yang, Seth Underwood, You-Soo Chang,

A. Rosati & T. Delworth (GFDL)

National Oceanic and Atmospheric Administration
Geophysical Fluid Dynamics Laboratory
Princeton, NJ 08542
<http://www.gfdl.noaa.gov>





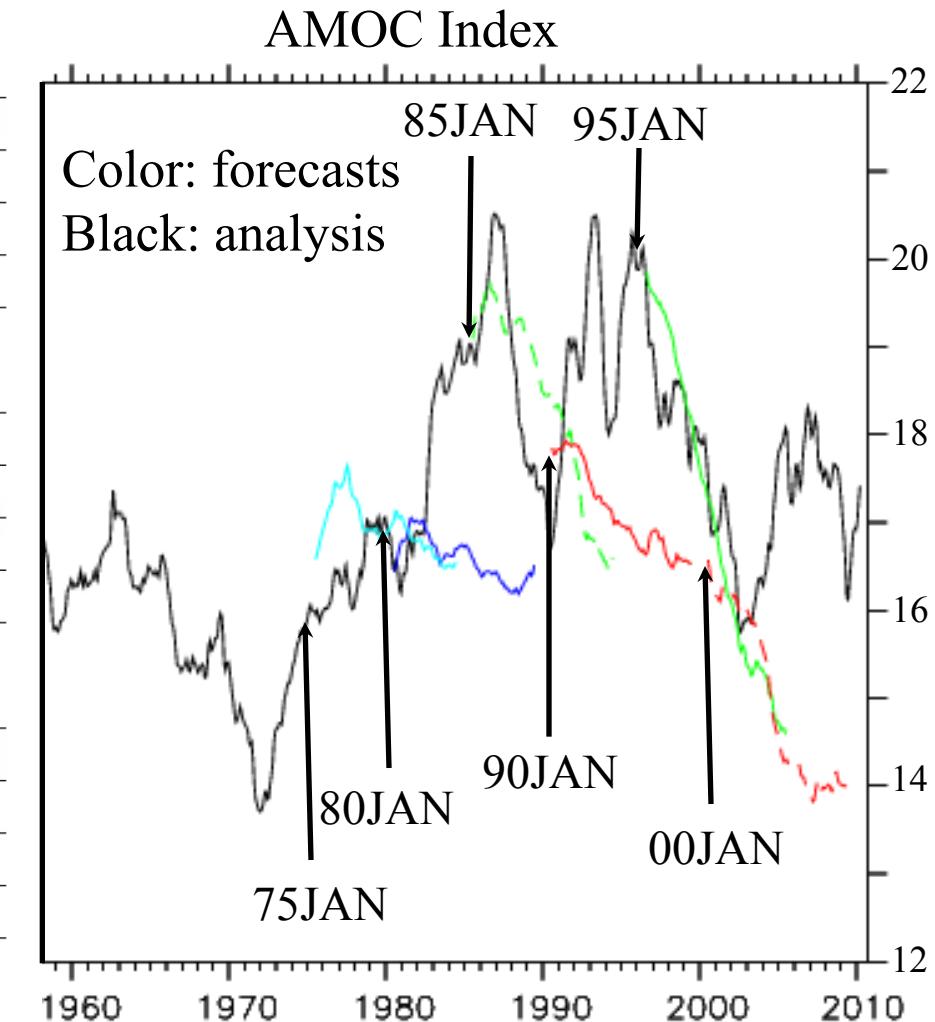
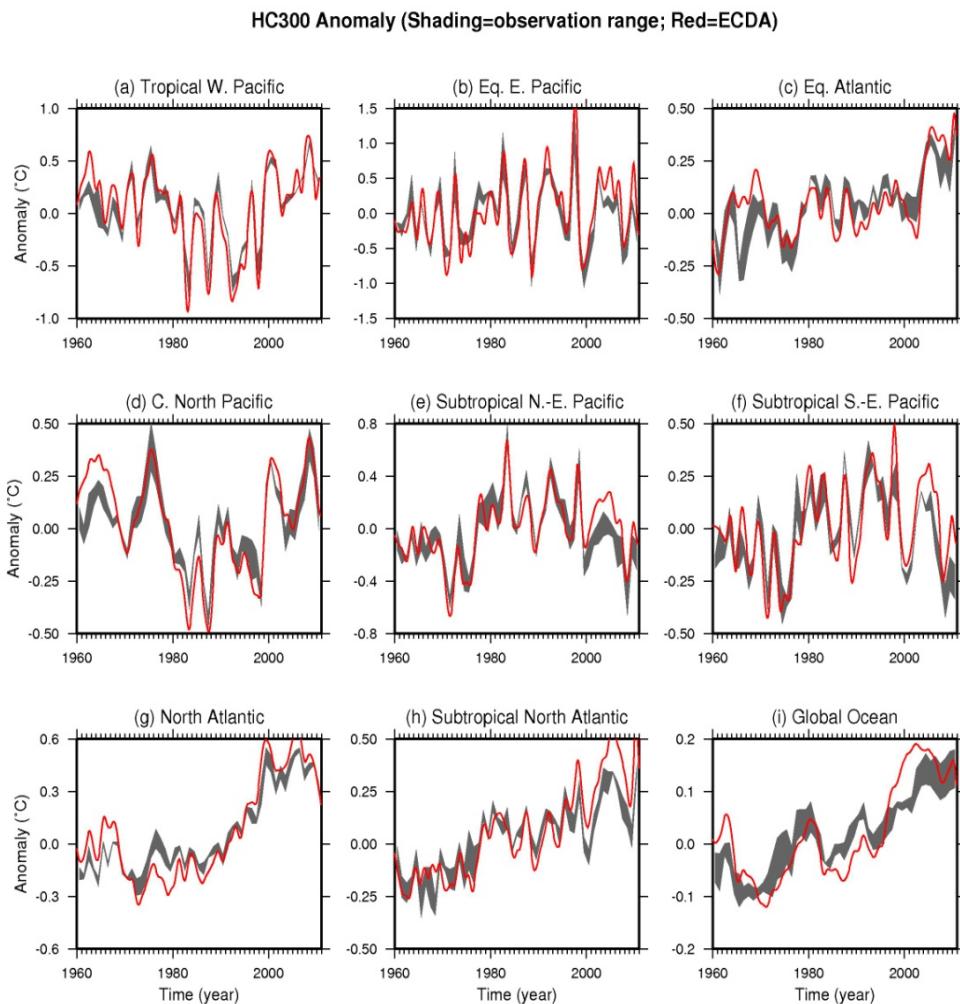
OUTLINE

1. Model bias analysis: parameter errors and climate drift in coupled models
2. The importance of sufficiently observation-constrained model states for coupled model parameter estimation – demonstrated in a simple model
3. The importance of allowing model parameters to geographically vary for coupled model parameter estimation – results from an intermediate coupled model
4. Preliminary results from the GFDL CM2.1 model — Sensitivity studies & twin experiments
5. Summary, discussions and future directions





1. Model bias analysis (1): Model drift in decadal prediction with the GFDL's ECDA system



(Y.-S. Chang et al. 2012)





1. Model bias analysis (2): parameter errors and model bias

- ✓ A numerical model is a discretized version of a set of budget equations for moment, heat, moisture, salt and other tracers including physics:

$$\underbrace{\frac{\partial}{\partial t} \begin{pmatrix} \text{moment} \\ \text{heat} \\ \text{other tracers} \end{pmatrix}}_{\text{dynamical core}} = \begin{pmatrix} \text{Advection} + \\ P. \text{ grad. force} + \\ \text{Coriolis} + \dots \end{pmatrix} + \underbrace{\text{internal physics} + \text{exchanged f luxes}}_{\text{Parameterization}}$$

- ✓ Three possible sources make a numerical model biased:

$$\begin{pmatrix} \text{Model} \\ \text{bias} \end{pmatrix} = \underbrace{\begin{pmatrix} \text{Dynamical core} \\ \text{bias} \end{pmatrix}}_{\text{model built-in 'structural' errors}} + \underbrace{\begin{pmatrix} \text{Physical scheme} \\ \text{bias} \end{pmatrix}}_{\text{adj usable by observations?}} + \begin{pmatrix} \text{Given model structure, parameter-derived} \\ \text{bias} \end{pmatrix}$$



2. The importance of observation-constrained model states

(1): Parameter Estimation Theory

- ✓ Ignore the model bias caused by dynamical core and physical scheme:

$$\begin{pmatrix} \text{Model} \\ \text{bias} \end{pmatrix} = \underbrace{\begin{pmatrix} \text{Dynamical core} \\ \text{bias} \end{pmatrix}}_{\text{model built-in structure errors}} + \underbrace{\begin{pmatrix} \text{Physical scheme} \\ \text{bias} \end{pmatrix}}_{\text{adjustable by observations?}} + \begin{pmatrix} \text{Model parameter} \\ \text{error} \end{pmatrix}.$$

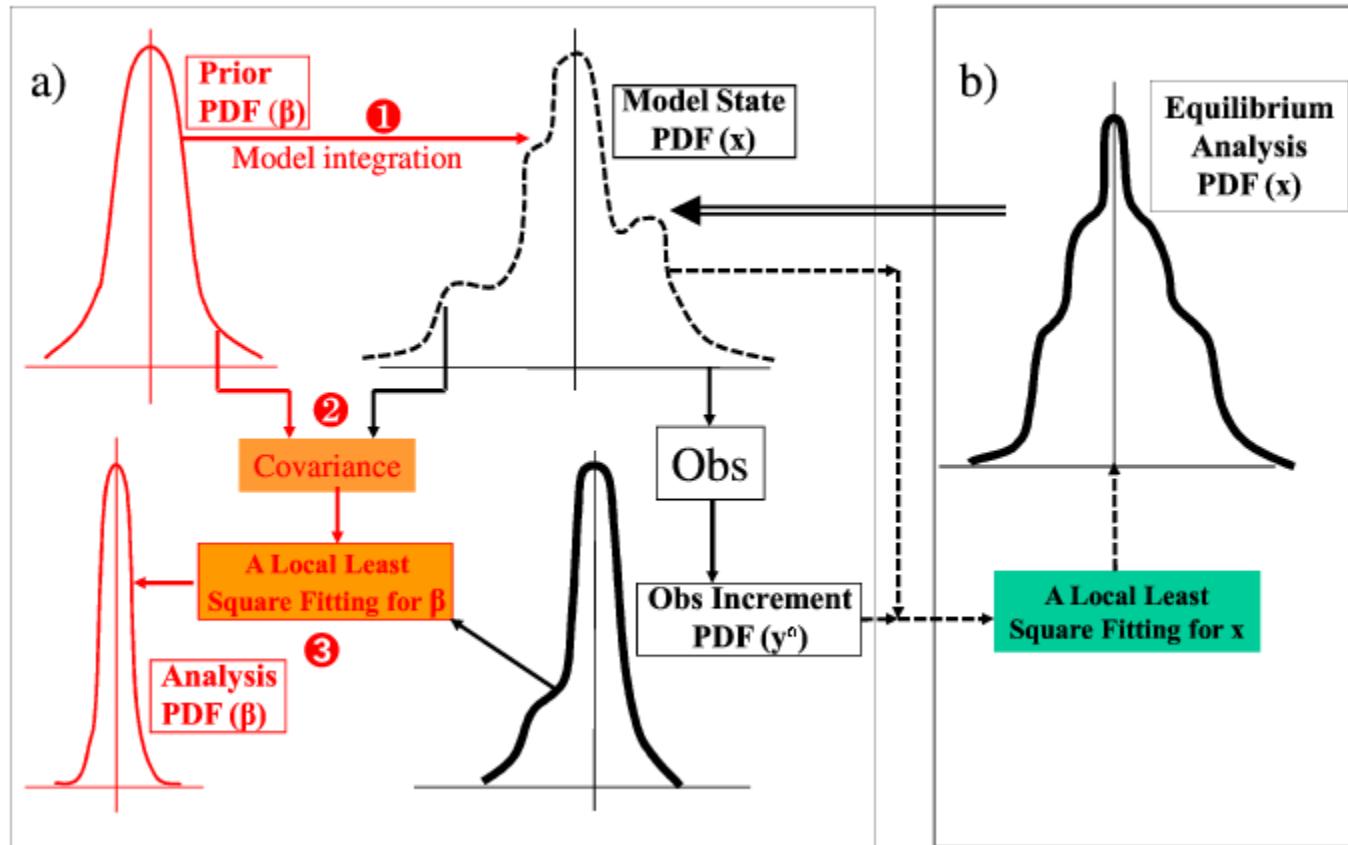
- ✓ Expand model control variables to include model parameters β : $\partial \mathbf{x}_t / \partial t = \mathbf{f}(\mathbf{x}_t, \beta, t) + \mathbf{G}(\mathbf{x}_t, \beta, t) \mathbf{w}_t$
- ✓ Expand Bayes' rule to include the contributions of parameter errors for model uncertainties:

$$p(\mathbf{x}_t, \beta_t | \mathbf{Y}_t) = p[\mathbf{y}_t | (\mathbf{x}_t, \beta_{t-1})] p[(\mathbf{x}_t, \beta_{t-1}) | \mathbf{Y}_{t-1}] / p(\mathbf{y}_t | \mathbf{Y}_{t-1})$$

- ✓ A linear regression $\Delta \beta_t = \text{Cov}[\beta_{t-1}, y(x_t)] / \sigma_m^2 * \Delta y^o$ to implement the estimation of $p(\mathbf{x}_t, \beta_t | \mathbf{Y}_t)$. Determined by x_t , $\text{Cov}[\beta_{t-1}, y(x_t)]$ projects Δy^o onto β .



2. The importance of observation-constrained model states (2): Delay parameter estimation until equilibrium of state estimation



2. The importance of observation-constrained model states

(3): Comparison on a simple PE case

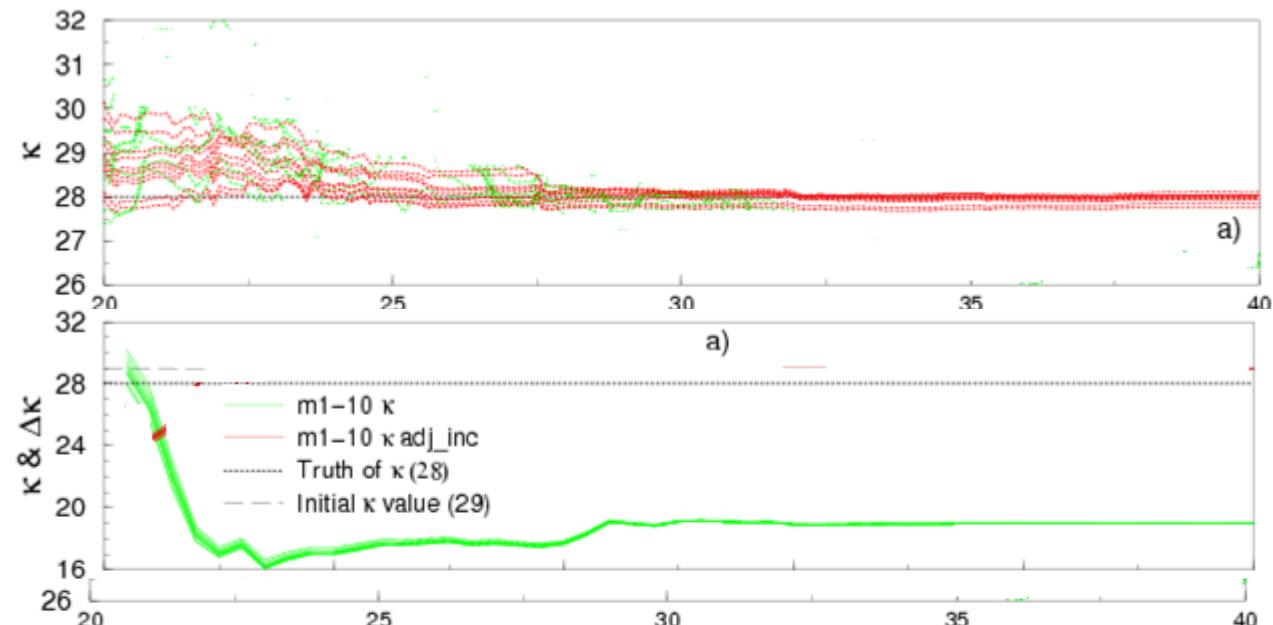
Simple coupled model

By x_2 - w interaction:

$$\begin{aligned}\frac{dx_1}{dt} &= -\alpha x_1 + \alpha x_2 \\ \frac{dx_2}{dt} &= -x_1 x_3 + \\ &\quad (1 + c_1 w) \kappa x_1 - x_2 \\ \frac{dx_3}{dt} &= x_1 x_2 - b x_3 \\ O_m \frac{dw}{dt} &= c_2 x_2 - O_d w + \\ S_m + S_s \cos(2\pi / S_{pd})\end{aligned}$$

Identical twin experiment:

- ✓ Using x_1 obs to estimate κ
- ✓ Obs are produced by $\kappa = 28$
- ✓ Assimilation model ensemble starts with $\kappa = 29 + \eta(0, 1)$





4. The importance of allowing model parameters to geographically vary for coupled model parameter estimation (Geographic Dependent Parameter Optimization, GPO)

A summary from 2 papers:

1. Wu, X., S. Zhang, Z. Liu, A. Rosati, T. Delworth, and Y. Liu, 2012: Impact of geographic dependent parameter optimization on climate estimation and prediction: simulation with an intermediate coupled model. *Mon. Wea. Rev.* doi: 10.1175/MWR-D-11-00298.1
2. Wu, X., S. Zhang, Z. Liu, A. Rosati, T. Delworth, 2012: A study of impact of the geographic dependence of observing system on parameter estimation with an intermediate coupled model. *Clim Dyn.* Doi:10.1007/s00382-012-1385-1



4.GPO (1): An intermediate coupled model(1) – Eqs.

Atmosphere

$$\text{Streamfunction } \psi: \frac{\partial q}{\partial t} + J(\psi, q) = \begin{cases} \lambda(T_o - \mu\psi) & \text{ocean} \cdot \text{surface} \\ \lambda(T_l - \mu\psi) & \text{land} \cdot \text{surface} \end{cases}$$

$(q = \beta y + \nabla^2 \psi)$

Land

$$\text{Temperature } T_l: m \frac{\partial}{\partial t} T_l = -K_L T_l + A_L \nabla^2 T_l + s(\tau, t) + C_l (T_l - \mu\psi)$$

Ocean

$$\text{Streamfunction } \varphi: \frac{\partial}{\partial t} \left(-\frac{\varphi}{L_0^2} \right) + \beta \frac{\partial}{\partial x} \varphi = \gamma \nabla^2 \psi - K_q \nabla^2 \varphi$$

$$\text{Temperature } T_o: \frac{\partial}{\partial t} T_o + u \frac{\partial T_o}{\partial x} + v \frac{\partial T_o}{\partial y} - K_h \varphi = -K_T T_o + A_T \nabla^2 T_o + s(\tau, t) + C_o (T_o - \mu\psi)$$

$L_0^2 = g' h_0 / f^2$

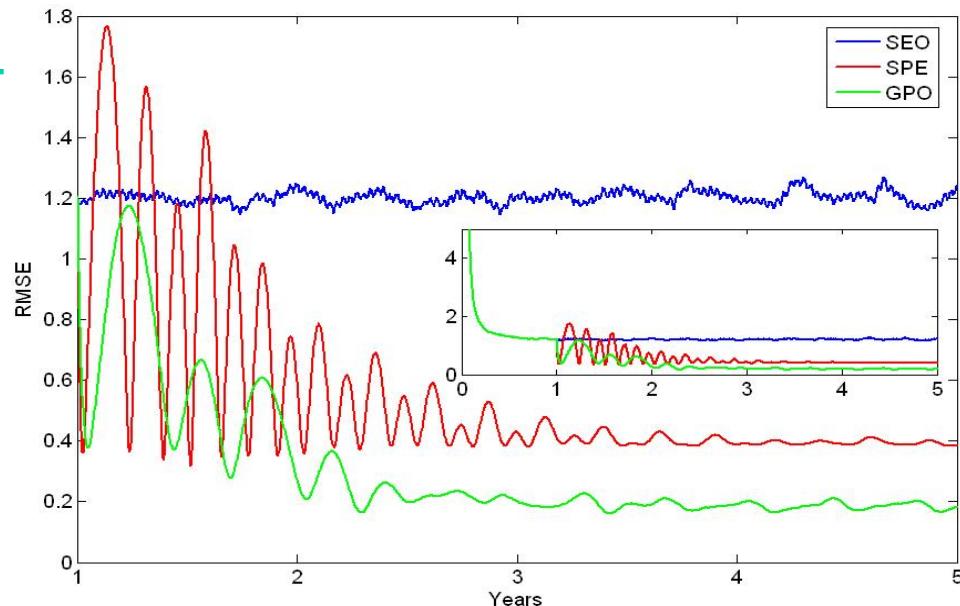
Here L_0 represents oceanic deformation radius, computed from $L_0^2 = g' h_0 / f^2$ and $s(\tau, t)$ represents solar forcings, others follow conventional notation.



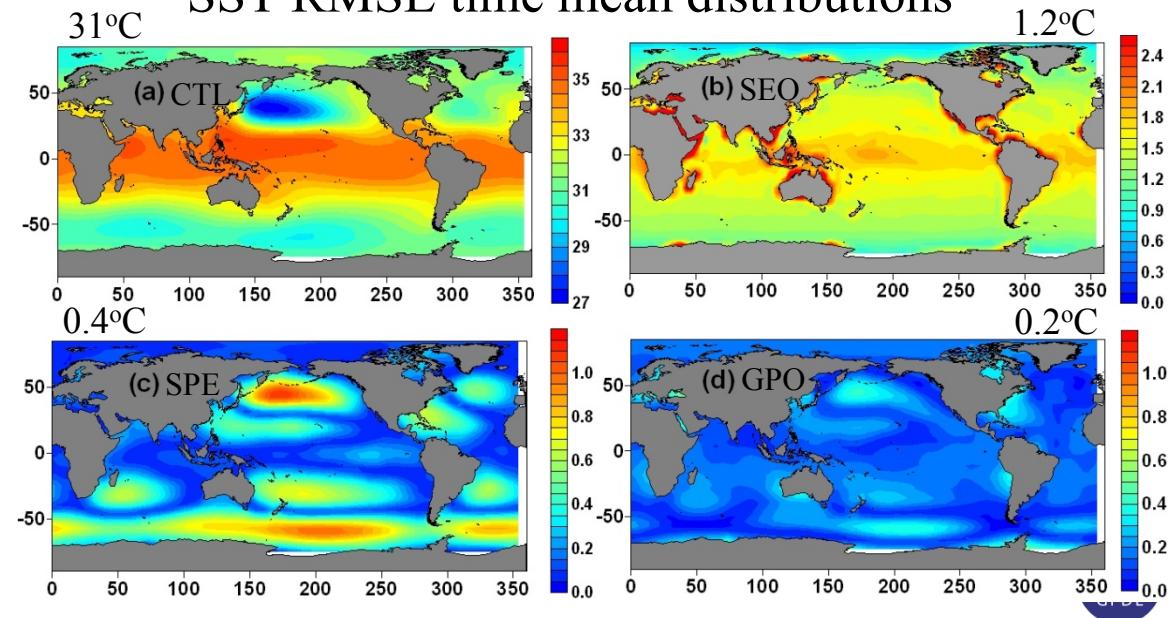
4.GPO (2): Simple case – SST obs optimize K_T

- ✓ All parameters (totally 10) are biased (10% more than truth values) in the CTL run (51 yrs).
- ✓ K_T is perturbed in the model ensemble.
- ✓ State estimation only (SEO) is performed in all model components (4/day for Atm, daily for Ocn) for 51 years.
- ✓ Single-valued parameter estimation (SPE) of K_T using SST obs is performed after 1-year SEO (for 50 yrs).
- ✓ Geographic-dependent parameter optimization (GPO) of K_T is performed after 1-year SEO (for 50 yrs).
- ✓ Parameter ensemble is subject to an inflation scheme.

Time series of SST global mean RMSEs



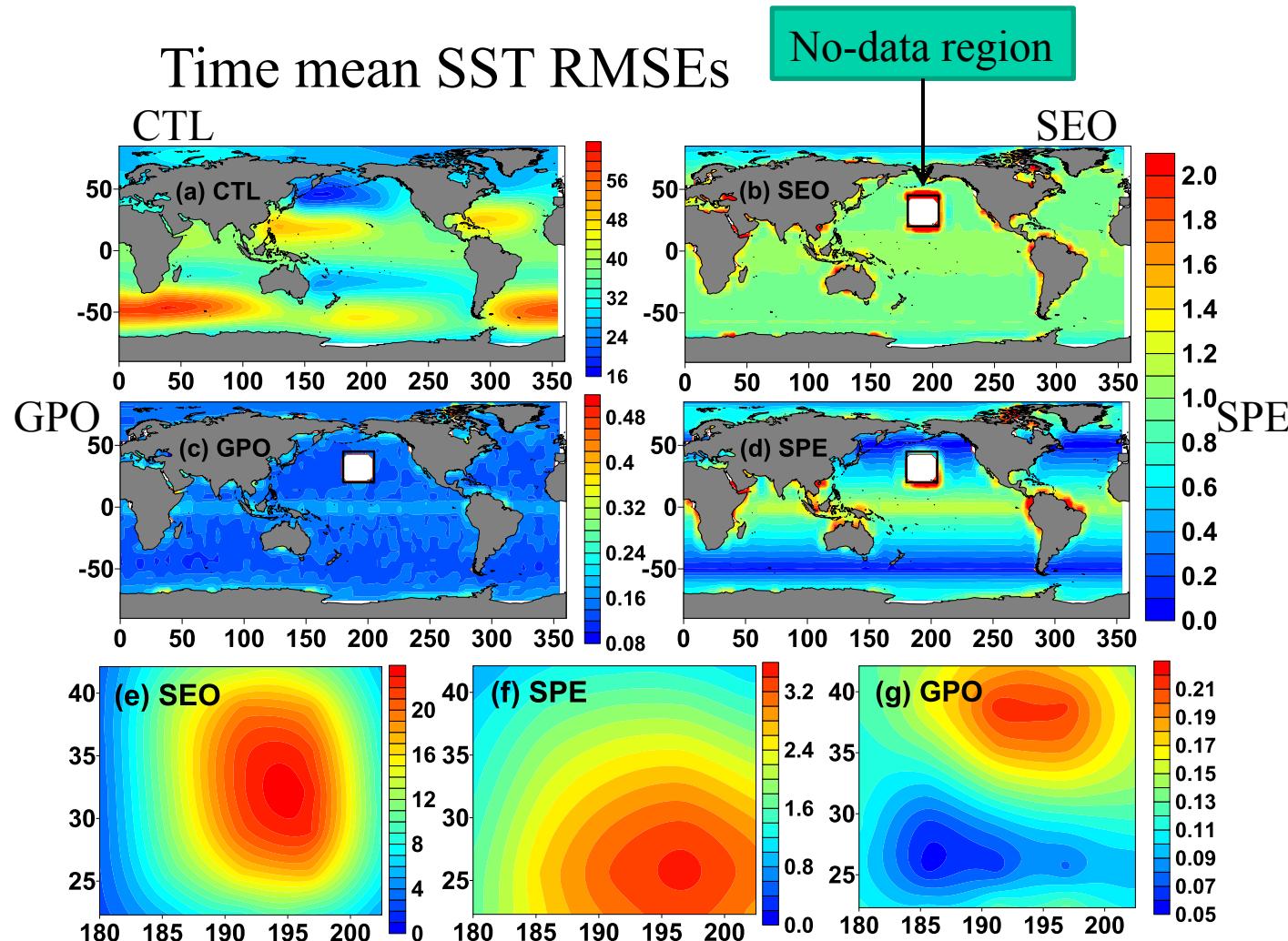
SST RMSE time mean distributions





4.GPO (4): Impact of Geographic-dependent Observing System(2) – Experiment with no-data region ($SST^{\text{obs}} \rightarrow K_T$)

- ✓ Single-valued Parameter Estimation (SPE) reduces the maximum error by 87% from SEO (from 28 to 3.6).
- ✓ Geographic-dependent Parameter Optimization reduces the maximum error by 94% from SPE (from 3.6 to 0.23).

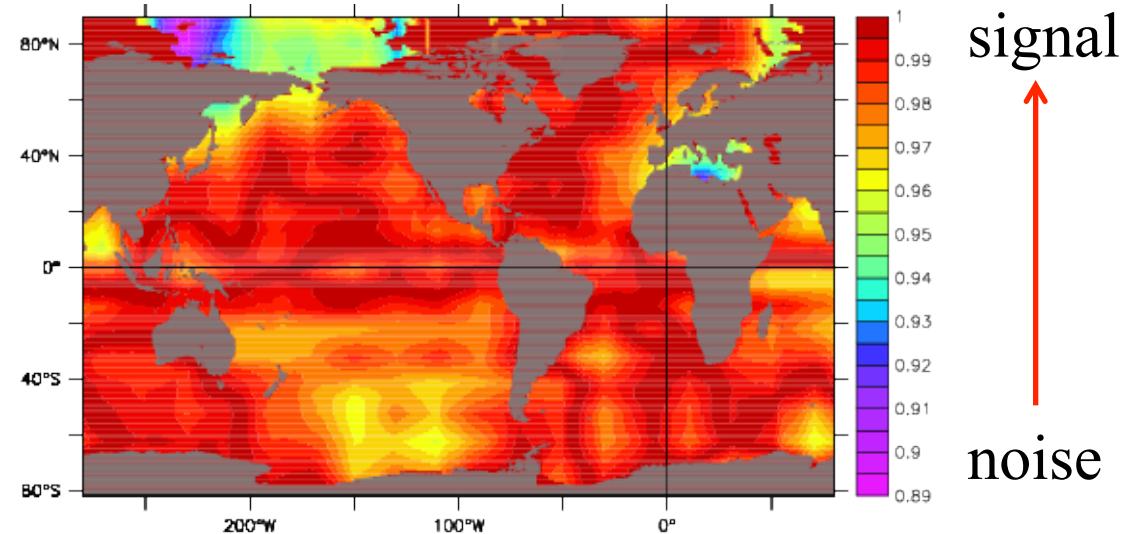




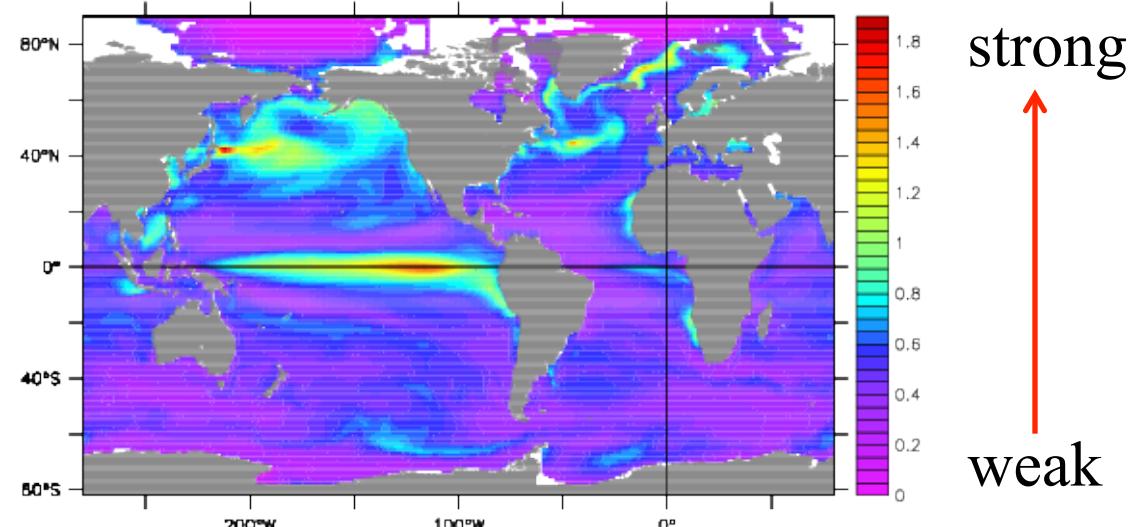
5.GFDL's CM2 PE twin experiment(1): GPO-optimized α – the air-sea transfer coefficient (Beljaars 1994)

Signal-to-noise ratio
of optimized α :

$$[1 - (\alpha - \alpha_{\text{truth}}) / \alpha_{\text{guess}}]$$

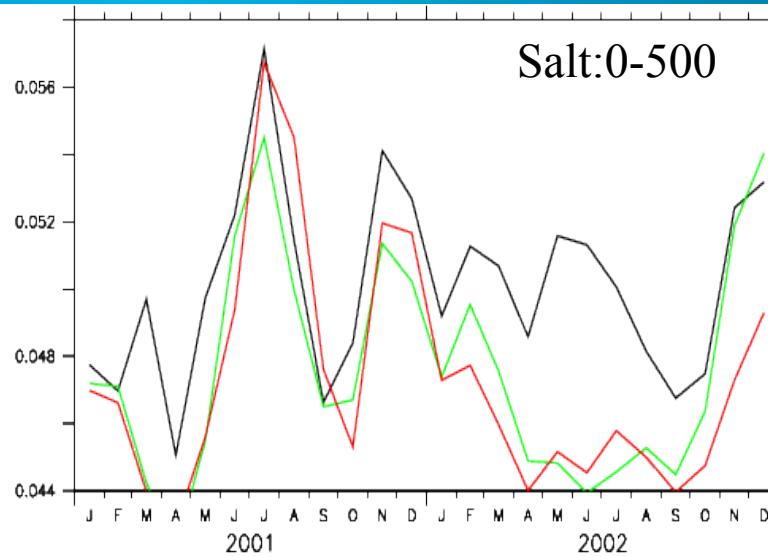
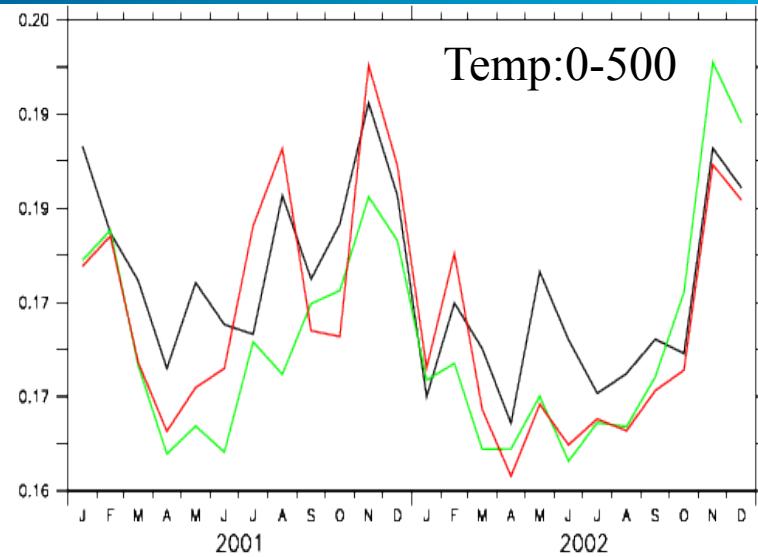


The sensitivities of
SST w.r.t. α





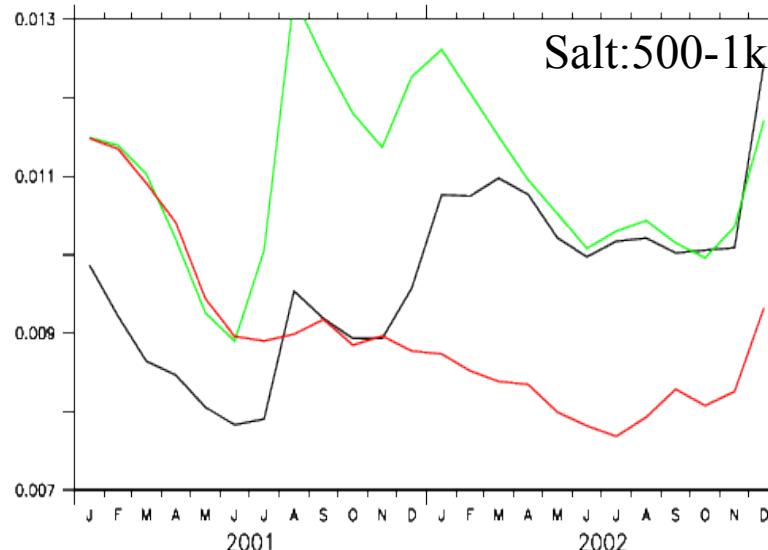
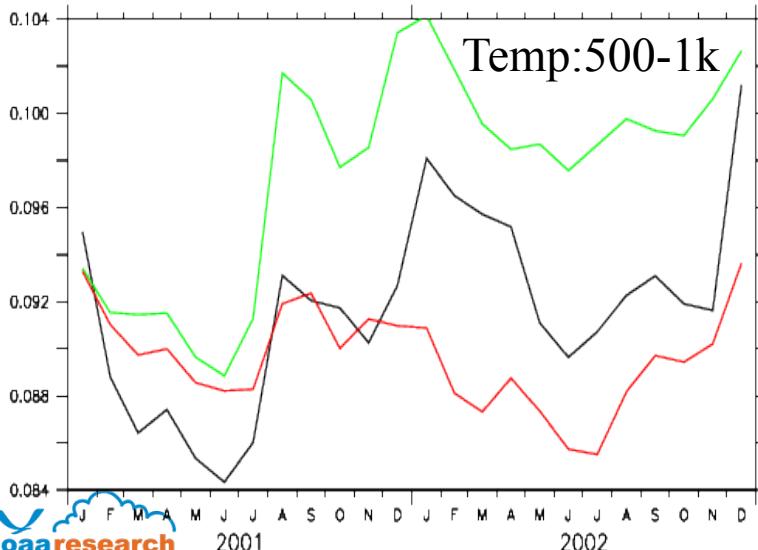
5.GFDL's CM2 PE twin experiment(2): Impact of GPO on oceanic analysis quality: RMSE



— ECDA

— SPE

— GPO





6. Summary and future work

- ✓ The model drift in decadal climate predictions can be relaxed by optimizing coupled model parameters using observations.
- ✓ Enhancing the signal-to-noise ratio of state-parameter covariances & eliminating the noises in the observing system is the key for successful coupled model parameter estimation, implemented by the scheme of data assimilation with enhancive parameter correction (DA_{EPC}) and Geographic-dependent Parameter Optimization (GPO).
- ✓ The ensemble coupled data assimilation with parameter estimation ($ECDA_{PE}$) has been implemented in the GFDL CM2 ($1^\circ \times 1^\circ$ Ocn + $2^\circ \times 2^\circ$ Atm) to develop a new generation of climate estimation and prediction system. Here twin experiments show promising results.
- ✓ Further examination is required to understand the impacts of GPO on climate analysis and predictions.
- ✓ Further studies are required for coupling parameter-estimation using a medium observations to optimize other media model parameters.

